Decentralized Adaptive Control for a Class of Large-Scale Nonlinear Systems with Unknown Interactions

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Abstract: This paper presents a decentralized adaptive controller for a class of large-scale nonlinear systems with unknown subsystems and interactions. A direct adaptive controller is devised based on Lyapunov stability analysis so that the stability of the closed loop system is guaranteed by introducing a suitably driven adaptive rule. The adaptive controller proposed in this paper can guarantee the stability of the closed-loop system without knowing the sign of the controller coefficient. To show the effectiveness of the proposed decentralized adaptive controller, a nonlinear system is chosen as a case study. Simulation results are very promising.

Key Words: Adaptive control and Decentralized nonlinear system

1 INTRODUCTION

In the past decades, there has been an increased attention in the development theories for large-scale systems. For large-scale systems, decentralized control can often provide better performance over centralized control [l]. For this reason, an increasing amount of attention is being directed towards decentralized control to extend the class of systems to which it is applicable [2], [3]. The difficulty and uncertainty in measuring parameter values within a large-scale system may call for adaptive techniques. Since these restrictions include a large group of applications, a variety of decentralized adaptive techniques has been developed. Model reference adaptive control (MRAC) based designs for decentralized systems have been studied in [4]–[6] for the continuous time case. Decentralized adaptive controllers for robotic manipulators were presented in [7] and [8], while a scheme for nonlinear subsystems with a special class of interconnections was formulated in [9]. Knowing that most of physical large-scale systems are nonlinearly coupled to the dynamics of the processes, the researchers are still trying to control these systems [10], [13]. Mostly, they either investigate subsystems which are linear in a set of unknown parameters i.e. [13], or they consider isolated subsystems to be known, i.e. [12, [14]. For most practical applications, the linear control synthesis is applicable to linearized models of large-scale systems. However, this only guarantees stability in a region about the operating point and possibly degradation in performance and instability over a large domain of operation. In [10] - [13], some decentralized nonlinear controllers for large-scale systems have been developed. For example, decentralized adaptive controllers are designed under the assumption that the isolated subsystems is known in [11], [12] and in [13], the subsystems with unknown parameter were considered linear in a set of unknown parameters.

It has been shown that the adaptive controller proposed in [13] can guarantee the stability of the closed-loop system when the sign of the controller coefficient is known.

Our objective is to present adaptive controllers for a class of decentralized systems with unknown nonlinear subsystems and unknown interactions. The stability of the closed-loop system is guaranteed by Lyapunov's stability theory and the proposed decentralized adaptive control scheme ensures that all signals in the closed-loop system be bounded and the tracking error goes asymptotically to zero without the requirement that the sign of the controller coefficient should be known in advance. In [15] we presented an adaptive controller for a class of affine nonlinear decentralized large-scale systems. This paper considers a more general class of these systems in which constraints of the subsystems' interactions have been relaxed.

This paper is organized as follows: In Section 2, the details of the problem statement and derivation of the error dynamics for the decentralized system are described. Section 3 presents the main results of decentralized adaptive control for each subsystem using only local information and stability analysis for composite system. An illustrative example is then used in Section 4 to demonstrate the effectiveness of the decentralized adaptive technique and finally Section 5 concludes the paper.

2 PROBLEM FORMULATION AND DERIVATION OF THE ERROR DYNAMICS

A large-scale nonlinear system comprised of N interconnected subsystems, is considered. The ith subsystem (S_i), which is assumed to be single-input–single-output, is given as

$$\begin{aligned}\dot{\mathbf{x}}_i &= \mathbb{F}_i(\mathbf{x}_1,\ldots,\mathbf{x}_N) + g_i(\mathbf{x}_i)u_i, \\ y_i &= h_i(\mathbf{x}_1,\ldots,\mathbf{x}_N),\end{aligned} \tag{1}$$

where $\mathbf{x}_i = [x_{i,1}, x_{i,2},\ldots,x_{i,n_i}]^T$, $1 \le i \le N$ is state vector, $\mathbf{x} = [\mathbf{x}_1, \mathbf{x}_2,\ldots,\mathbf{x}_N]^T$ is full state of the overall system, $\mathbb{F}_i(.)$, $g_i(.) \in \mathbb{R}^{n_i}$, $h_i(.) \in \mathbb{R}$, are unknown smooth functions, $u_i \in \mathbb{R}$ and $y_i \in \mathbb{R}$ are respectively the input and output of the ith subsystem. If each subsystem has strong relative degree m_i, then the output dynamics may be rewritten as [16]

$$y_i^{(m_i)} = \sum_{k=1}^{l} \alpha_{i,k} f_{i,k}(\mathbf{x}_i) + \beta_i u_i + \Delta_i(\mathbf{x}_1,\ldots,\mathbf{x}_N) \tag{2}$$

where $y_i^{(m_i)}$ is the m_i th time derivative of y_i and $\alpha_{i,k}$, β_i are unknown parameters. To design the controller, in Eq. (2) we do not need to know the sign of β_i in all subsystems.

Assumption 1. The interconnection $\Delta_i(\mathbf{x}_1,\ldots,\mathbf{x}_N)$ is bounded by $|\Delta_i(\mathbf{x}_1,\ldots,\mathbf{x}_N)| \le \rho_i$, where ρ_i is unknown and $\rho_i > 0$.

Now define the tracking error $e_i = r_i - y_i$ for S_i, where r_i is the desired output trajectory and y_i is the output of ith subsystem.

Our objective is to design an adaptive control system for each subsystem which will cause the output y_i to track the desired output trajectory r_i in the presence of interconnections and, using only local measurements. This requirement leads to the following assumption.

Assumption 2. The desired output trajectory and its derivatives $r_i,\ldots,r_i^{(m_i)}$ for the ith subsystem S_i are measurable and bounded.

Let the output error vector for the ith subsystem be defined by $\mathbf{e}_i = [e_i, \dot{e}_i,\ldots,e_i^{(m_i-1)}]^T$ and write the time derivative of $\mathbf{e}_i$ as

$$\dot{\mathbf{e}}_i = [\dot{e}_i, e_i^{(2)},\ldots,e_i^{(m_i)}]^T \tag{3}$$

The error dynamics may be expressed as

$$e_i^{(m_i)} = r_i^{(m_i)} - y_i^{(m_i)} \tag{4}$$

It is desired that the output error of the ith subsystem follows $e_i^{(m_i)} + a_{i,m_i-1} e_i^{(m_i-1)} + \ldots + a_{i,0} e_i = 0$, where the coefficients are chosen so that each $L_i(s) = s^{m_i} + a_{i,m_i-1} s^{m_i-1} + \ldots + a_{i,0}$ has its roots in the open left-half plane. Now use (2) and (4) to obtain

$$e_i^{(m_i)} = r_i^{(m_i)} - \sum_{k=1}^{l} \alpha_{i,k} f_{i,k}(\mathbf{x}_i) - \beta_i u_i - \Delta_i \tag{5}$$

3 DECENTRALIZED ADAPTIVE CONTROLLER AND STABILITY ANALYSIS

This section presents an adaptive controller for (2) with unknown interconnection functions. An adaptive algorithm is defined to estimate $\alpha_{i,k}$ with $\hat{\alpha}_{i,k}$, β_i with $\hat{\beta}_i$, and ρ_i with $\hat{\rho}_i$ and compensate the unknown interactions. Define a controller which compensates for the dynamics of each subsystem. For the ith subsystem, the controller is defined by

$$u_i = \frac{v_i}{\hat{\beta}_i} \tag{6}$$

where the signal v_i is defined as

$$\begin{aligned} v_i \triangleq &\left(a_{i,0} e_i + a_{i,1}\dot{e}_i + a_{i,2} e_i^{(2)} + \ldots + a_{i,m_i-1} e_i^{(m_i-1)}\right) \\ &- \sum_{k=1}^{l} \hat{\alpha}_{i,k} f_{i,k}(\mathbf{x}_i) + r_i^{(m_i)} + \hat{\rho}_i \operatorname{sgn}(\mathbf{e}_i^T P_i \mathbf{b}_i^T), \end{aligned} \tag{7}$$

where $\mathbf{b}_i$ and P_i are given in (13) and (14) respectively. Substitute (6) into (5) to obtain

$$e_i^{(m_i)} = r_i^{(m_i)} - \sum_{k=1}^{l} \alpha_{i,k} f_{i,k}(\mathbf{x}_i) - \frac{\beta_i}{\hat{\beta}_i} v_i - \Delta_i \tag{8}$$

The third term, $\frac{\beta_i}{\hat{\beta}_i}$, in (8) is equal to:

$$\frac{\beta_i}{\hat{\beta}_i} = 1 - \frac{\hat{\beta}_i - \beta_i}{\hat{\beta}_i} = 1 - \frac{\tilde{\beta}_i}{\hat{\beta}_i} \tag{9}$$

where the $\tilde{\beta}_i$ is defined as $\tilde{\beta}_i = \hat{\beta}_i - \beta_i$. Use (8) and (9) to obtain:

$$e_i^{(m_i)} = r_i^{(m_i)} - \sum_{k=1}^{l} \alpha_{i,k} f_{i,k}(\mathbf{x}_i) - v_i + \frac{\tilde{\beta}_i}{\hat{\beta}_i} v_i - \Delta_i \tag{10}$$

From (7) and (10), equation (10) becomes:

$$\begin{aligned} e_i^{(m_i)} = &\sum_{k=1}^{l} \tilde{\alpha}_{i,k} f_{i,k}(\mathbf{x}_i) \\ &- \left(a_{i,0} e_i + a_{i,1}\dot{e}_i + \ldots + a_{i,m_i-1} e_i^{(m_i-1)}\right) \\ &- \hat{\rho}_i \operatorname{sgn}(\mathbf{e}_i^T P_i \mathbf{b}_i^T) + \frac{\tilde{\beta}_i}{\hat{\beta}_i} v_i - \Delta_i, \end{aligned} \tag{11}$$

where the $\tilde{\alpha}_{i,k}$ is defined as $\tilde{\alpha}_{i,k} = \hat{\alpha}_{i,k} - \alpha_{i,k}$.

Substituting (11) in (3), the error dynamics (3) can be written in a matrix form as:

$$\dot{\mathbf{e}}_i = A_i\mathbf{e}_i + \mathbf{b}_i\Big(\sum_{k=1}^{l}\tilde{\alpha}_{i,k} f_{i,k}(\mathbf{x}_i) - \hat{\rho}_i \,\mathrm{sgn}(\mathbf{e}_i^T P_i \mathbf{b}_i^T) + \frac{\tilde{\beta}_i}{\hat{\beta}_i} v_i - \Delta_i\Big) \tag{12}$$

where the Hurwitz matrix A_i and vector $\mathbf{b}_i$ are

$$A_i = \begin{bmatrix} 0 & 1 & 0 & . & . & . & 0 \\ 0 & 0 & 1 & . & . & . & 0 \\ . & . & . & . & & & . \\ . & . & . & & . & & . \\ . & . & . & & & . & . \\ 0 & 0 & 0 & . & . & . & 1 \\ -a_{i,0} & -a_{i,1} & -a_{i,2} & . & . & . & -a_{i,m_i-1} \end{bmatrix},$$

$$\mathbf{b}_i = [0\ \ 0\ \ \ldots\ \ 1]^T. \tag{13}$$

Since A_i is Hurwitz, a unique positive definite solution P_i to the following Lyapunov equation exists

$$A_i^T P_i + P_i A_i = -Q_i \tag{14}$$

where the matrix Q_i is positive definite.

Consider the following update laws:

$$\dot{\hat{\alpha}}_{i,k} = -\gamma_{\alpha_i} f_{i,k}(\mathbf{x}_i)\mathbf{e}_i^T P_i \mathbf{b}_i^T \tag{15}$$

$$\dot{\hat{\beta}}_i = -\gamma_{\beta_i}\mathbf{e}_i^T P_i \mathbf{b}_i^T v_i / \hat{\beta}_i \tag{16}$$

$$\dot{\hat{\rho}}_i = \gamma_{\rho_i}\left|\mathbf{e}_i^T P_i \mathbf{b}_i\right| \tag{17}$$

where $\gamma_{\alpha_i}, \gamma_{\beta_i}, \gamma_{\rho_i} > 0$ are constant design parameters. The main results of this paper are now summarized in the following theorem.

Theorem: Given the error dynamical system (12) for the decentralized system (1) with a reference model satisfying Assumption 2 and the interaction between subsystems satisfying Assumption 1, then the control law (6) with adaptation laws (15) – (17) makes the tracking error asymptotically converge to zero and all signals in the closed loop system bounded.

Proof: Consider the following Lyapunov function

$$V = \sum_{i=1}^{N}\left(V_{i,1} + V_{i,2}\right) \tag{18}$$

With

$$V_{i,1} = \mathbf{e}_i^T P_i \mathbf{e}_i \tag{19}$$

$$V_{i,2} = \frac{\sum_{k=1}^{l}\tilde{\alpha}_{i,k}^2}{\gamma_{\alpha_i}} + \frac{\tilde{\beta}_i^2}{\gamma_{\beta_i}} + \frac{\tilde{\rho}_i^2}{\gamma_{\rho_i}} \tag{20}$$

where $\tilde{\alpha}_{i,k} = \hat{\alpha}_{i,k} - \alpha_{i,k}$, $\tilde{\beta}_i = \hat{\beta}_i - \beta_i$ and $\tilde{\rho}_i = \hat{\rho}_i$. $-\rho_i$ Use the definition of the error dynamic (12) to write the time derivative of $\dot{V}$ as

$$\begin{aligned}\dot{V} = \sum_{i=1}^{N}\Big[&\mathbf{e}_i^T\left(A_i^T P_i + P_i A_i\right)\mathbf{e}_i \\ &+ 2\mathbf{e}_i^T P_i \mathbf{b}_i \sum_{k=1}^{l}\tilde{\alpha}_{i,k} f_{i,k}(\mathbf{x}_i) \\ &+ 2\mathbf{e}_i^T P_i \mathbf{b}_i\left(-\hat{\rho}_i \,\mathrm{sgn}(\mathbf{e}_i^T P_i \mathbf{b}_i^T) + \frac{\tilde{\beta}_i}{\hat{\beta}_i} v_i - \Delta_i\right) + \dot{V}_{i,2}\Big]\end{aligned} \tag{21}$$

From (14), we have

$$\begin{aligned}\dot{V} = \sum_{i=1}^{N}\Big[&-\mathbf{e}_i^T Q_i \mathbf{e}_i \\ &+ 2\mathbf{e}_i^T P_i \mathbf{b}_i \sum_{k=1}^{l}\tilde{\alpha}_{i,k} f_{i,k}(\mathbf{x}_i) \\ &+ 2\mathbf{e}_i^T P_i \mathbf{b}_i\left(-\hat{\rho}_i \,\mathrm{sgn}(\mathbf{e}_i^T P_i \mathbf{b}_i^T) + \frac{\tilde{\beta}_i}{\hat{\beta}_i} v_i - \Delta_i\right) + \dot{V}_{i,2}\Big]\end{aligned} \tag{22}$$

Furthermore, knowing that $\left|\Delta_i(\mathbf{x}_1, \ldots, \mathbf{x}_N)\right| \le \rho_i$, we can obtain the following upper bound for the time derivative of $\dot{V}$:

$$\begin{aligned}\dot{V} \le \sum_{i=1}^{N}\Big[&-\mathbf{e}_i^T Q_i \mathbf{e}_i + 2\mathbf{e}_i^T P_i \mathbf{b}_i \sum_{k=1}^{l}\tilde{\alpha}_{i,k} f_{i,k}(\mathbf{x}_i) \\ &-2\left|\mathbf{e}_i^T P_i \mathbf{b}_i\right|\hat{\rho}_i + 2(\mathbf{e}_i^T P_i \mathbf{b}_i)\frac{\tilde{\beta}_i}{\hat{\beta}_i} v_i + 2\left|\mathbf{e}_i^T P_i \mathbf{b}_i\right|\rho_i \\ &+\dot{V}_{i,2}\Big], \\ \le \sum_{i=1}^{N}\Big[&-\mathbf{e}_i^T Q_i \mathbf{e}_i + 2(\mathbf{e}_i^T P_i \mathbf{b}_i)\sum_{k=1}^{l}\tilde{\alpha}_{i,k} f_{i,k}(\mathbf{x}_i) \\ &-2\left|\mathbf{e}_i^T P_i \mathbf{b}_i\right|\tilde{\rho}_i + 2(\mathbf{e}_i^T P_i \mathbf{b}_i)\frac{\tilde{\beta}_i}{\hat{\beta}_i} v_i + \dot{V}_{i,2}\Big],\end{aligned} \tag{23}$$

From (18), (20) and (23), we can write

$$\begin{aligned}\dot{V} \le \sum_{i=1}^{N}\Big[&-\mathbf{e}_i^T Q_i \mathbf{e}_i + 2\sum_{k=1}^{l}\tilde{\alpha}_{i,k}\Big(\mathbf{e}_i^T P_i \mathbf{b}_i f_{i,k}(\mathbf{x}_i) + \frac{\dot{\hat{\alpha}}_{i,k}}{\gamma_{\alpha_i}}\Big) \\ &+ 2\tilde{\beta}_i\Big(\frac{\mathbf{e}_i^T P_i \mathbf{b}_i v_i}{\hat{\beta}_i} + \frac{\dot{\hat{\beta}}_i}{\gamma_{\beta_i}}\Big) - 2\tilde{\rho}_i\Big(\left|\mathbf{e}_i^T P_i \mathbf{b}_i\right| - \frac{\dot{\hat{\rho}}_i}{\gamma_{\rho_i}}\Big)\Big]\end{aligned} \tag{24}$$

Use the parameters adaptive rules (15) – (17), to obtain $\dot{V}$

$$\dot{V} \le \sum_{i=1}^{N} -\mathbf{e}_i^T Q_i \mathbf{e}_i \tag{25}$$

Using Barbalat's lemma, convergence of the tracking error to zero is guaranteed. This will make the convergence of the update laws, equations (15) – (17), possible. This completes the proof. Q.E.D.

Remark 1: The proposed method given in section 3 is apparently more general than the subsystems as considered in [15]. Results of the proposed controller to the inverted pendulum problem are fully presented in [15]. As we will show in next section, the controller exhibits faster response compared with that of [15], which confirms superiority of the this controller.

4 AN ILLUSTRATIVE EXAMPLE

In this section, an inverted pendulums connected by a spring [13], is used as a case study to illustrate the capability of the proposed decentralized adaptive control. Each pendulum may be positioned by a torque input u_i applied by a servomotor at its base. It is assumed that both θ_i and $\dot{\theta}_i$ (angular position and rate) are available to the ith controller for *i = 1, 2*. The nonlinear equations which describe the motion of the pendulums are defined by (26) where $x_{1,1}=\theta_1$ and $x_{2,1}=\theta_2$ are the angular displacements of the pendulums from vertical. The parameters $m_1=2kg$ and $m_2=2.5kg$ are the pendulum end masses, $j_1=0.5kg$ and $j_2=0.625kg$ are the moments of inertia, *k = 100N/m* is the spring constant of the connecting spring, *r =0.5m* is the pendulum height, *l=0.5m* is the natural length of the spring, and $g=9.81m/s^2$ is gravitational acceleration. The distance between the pendulum hinges is *b=0.4m*. A*, b<l* indicates that the pendulums repel one another when both are in the upright position [17]. Here we will attempt to regulated the angular positions to zero, so that $e_i=-\theta_i$ [i.e., $x_i^d=0, i=1,2$].

$$\begin{cases} \dot{x}_{1,1}=x_{1,2} \\ \dot{x}_{1,2}=\left(\frac{m_1 gr}{j_1}-\frac{kr^2}{4j_1}\right)\sin\left(x_{1,1}\right)+\frac{kr}{2j_1}\left(l-b\right) \\ \qquad +\frac{u_1}{j_1}+\frac{kr^2}{4j_1}\sin\left(x_{2,1}\right) \end{cases}$$
$$y_1=x_{1,1}$$
$$\begin{cases} \dot{x}_{2,1}=x_{2,2} \\ \dot{x}_{2,2}=\left(\frac{m_2 gr}{j_2}-\frac{kr^2}{4j_2}\right)\sin\left(x_{2,1}\right)-\frac{kr}{2j_2}\left(l-b\right) \\ \qquad +\frac{u_2}{j_2}+\frac{kr^2}{4j_2}\sin\left(x_{1,1}\right) \end{cases}$$
$$y_2=x_{2,1} \tag{26}$$

To show the effectiveness of the proposed method, two controllers are studied for the purpose comparison. We will first demonstrate how a simple decentralized proportional plus integral (PI) controller

$$u_i=20\left(e_i+\frac{1}{20}\int_0^t e_i d\tau\right) \qquad , i=1,2 \tag{27}$$

would control the system. We find that the pendulums exhibit undesirable response with relatively large oscillatory behavior due to the lack of damping as shown in Figs 1 - 2.

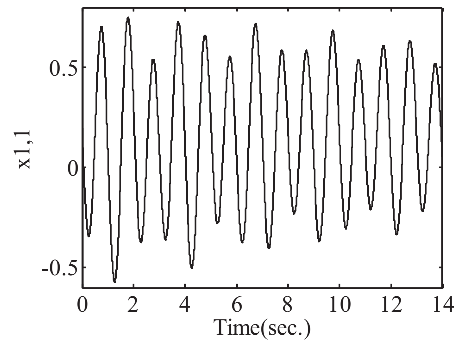

Fig. 1. PI controller for the first subsystem ($x_{1,1}=\theta_1$)

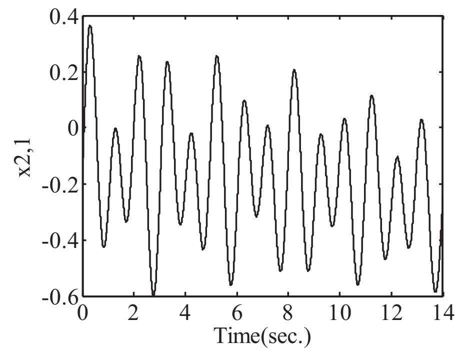

Fig. 2. PI controller for the second subsystem ($x_{2,1}=\theta_2$)

decentralized adaptive controller proposed in Section 3 is then applied to this system. The controller is taken as

$$u_i=\frac{1}{\hat{\beta}_i}\Big[\left(a_{i,0}e_i+a_{i,1}\dot{e}_i+\ldots+a_{i,m_i-1}e_i^{(m_i-1)}\right) \\ -\sum_{k=1}^{l}\hat{\alpha}_{i,k}f_{i,k}(\mathbf{x}_i)+r_i^{(m_i)}+\hat{\rho}_i\ \mathrm{sgn}(\mathbf{e}_i^T P_i \mathbf{b}_i^T)\Big], \tag{28}$$

where $\hat{\beta}_i, \hat{\alpha}_{i,k}, \hat{\rho}_i$ are updated by adaptive rules (15) – (17). The controller parameters are taken as $\gamma_{\alpha_i}=\gamma_{\beta_i}=10$, $\gamma_{\rho_i}=20$. Figures 3 - 4 show the simulation results for the designed controller and illustrate that, after a short transient period, the states track the given trajectories very closely.

Comparing the results in Figs. 1- 2 and 3- 4, it can be seen that the proposed decentralized adaptive controller presents desirable performance which confirms fast convergence of the adaptive parameters. The parameters $\hat{\alpha}_{1,1}, \hat{\alpha}_{1,2}, \hat{\beta}_1$, $\hat{\alpha}_{2,1}, \hat{\alpha}_{2,2}, \hat{\beta}_2$ and $\hat{\rho}_1, \hat{\rho}_2$, the adaptive parameters, are depicted in Figs. 5- 7 respectively. Figures 8 - 9 are also shown the history of the control input u_i , $i=1,2$. From figures 5- 9, it is interesting to note that (28) maintains a robust performance to a wide class of perturbations in the system dynamics, as long as the interactions are bounded. In this sense, the controllers guarantee robustness against modeled dynamics inaccuracies.

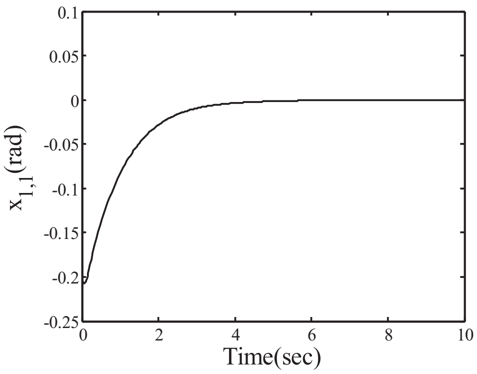

Fig. 3. Decentralized adaptive controller for the first subsystem ($x_{1,1} = \theta_1$)

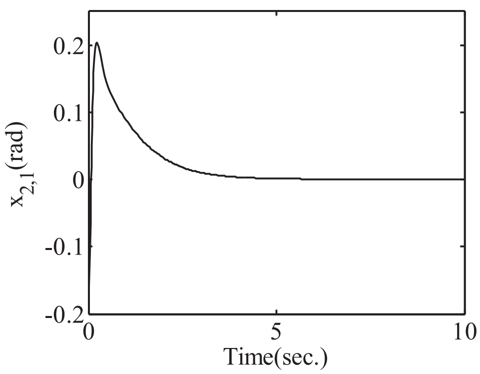

Fig. 4. Decentralized adaptive controller for the second subsystem ($x_{2,1} = \theta_2$)

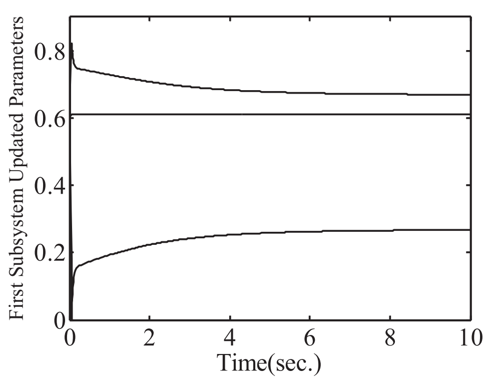

Fig. 5. Convergence of the first subsystem adaptive parameters $(\hat{\alpha}_{1,1}, \hat{\alpha}_{1,2}, \hat{\beta}_1)$

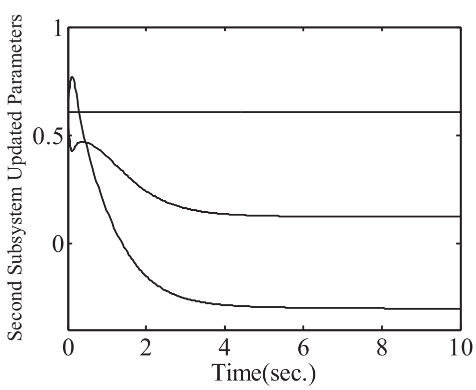

Fig. 6. Convergence of the second subsystem adaptive parameters $(\hat{\alpha}_{2,1}, \hat{\alpha}_{2,2}, \hat{\beta}_2)$

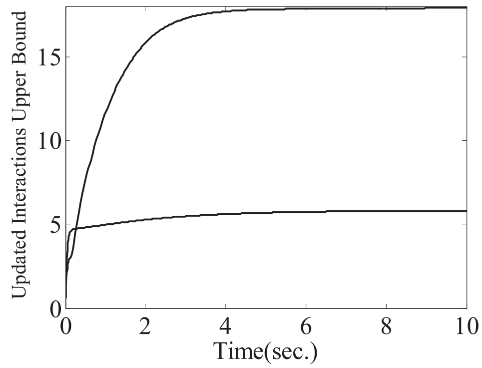

Fig. 7. Convergence of the interactions upper bounds $(\hat{\rho}_1, \hat{\rho}_2)$

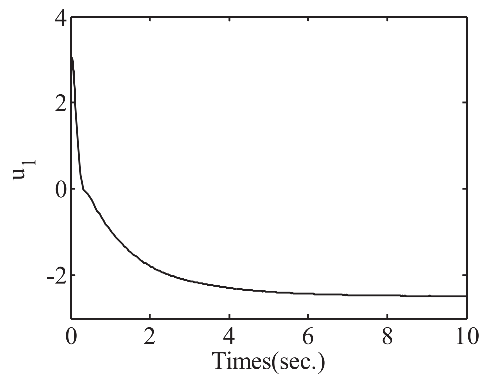

Fig. 8. Control input u_1 for the first subsystem

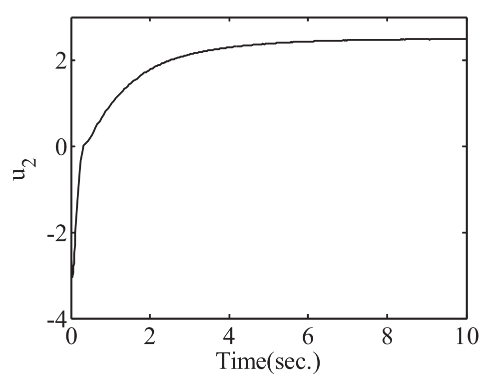

Fig. 9. Control input u_2 for the second subsystem

5 Conclusion

This paper introduced a decentralized adaptive controller for a class of large-scale nonlinear systems. This class consists of all such systems with unknown SISO subsystems and unknown interactions. The proposed adaptive controller ensured the closed-loop stability and convergence of the tracking errors asymptotically to zero. The stability analysis was performed using the Lyapunov's theory. The simulation results approved the validity of the proposed controller**.**

REFERENCES

[1] D. D. Siljak , Decentralized Control of Complex Systems. Mathematics in Science and Engineering,vol. 184, Academic Press, San Diego, 1991.

[2] C. Wen, Y. C. Soh, Decentralized Adaptive Control Using Integrator Backstepping, Automatica, vol. 33, no. 9, 1719-1724, 1997.

[3] M. C. Han, Y. H. Chen, Decentralized control design: uncertain systems with strong interconnections, Int. J. Control, vol. 61, no. 6, 1363-1385, 1995.

[4] P. A. Ioannou, Decentralized adaptive control of interconnected systems, IEEE Automat. Trans. Contr., vol. 31, no. 4, pp. 291–298, Apr.1986.

[5] D. T. Gavel and D. D. Siljak, Decentralized adaptive control: Structural conditions for stability, IEEE Trans. Automat. Contr., vol. 34, pp. 413–426, Apr. 1989.

[6] A. Datta, Performance improvement in decentralized adaptive control: A modified model reference scheme, IEEE Trans. Automat. Contr., vol. 38, pp. 1717–1722, Nov. 1993.

[7] L.-C. Fu, Robust adaptive decentralized control of robot manipulators, IEEE Trans. Automat. Contr., vol. 37, pp. 106–110, Jan. 1992.

[8] H. Seraji, Decentralized adaptive control of manipulators: Theory, simulation, and experimentation, IEEE Trans. Robot. Automat., vol. 5, pp. 183–201, 1989.

[9] S. Sheikholeslam and C. A. Desoer, Indirect adaptive control of a class of interconnected nonlinear dynamical systems, Int. J. Cont., vol. 57, no. 3, pp. 743–765, 1993.

[10] C. Wen, Decentralized adaptive regulation, IEEE Trans. Automatic Contr., vol. 39, pp. 2163–2166, Oct. 1994.

[11] L. Shi and S. K. Singh, Decentralized adaptive controller design for large-scale systems with higher order interconnections, IEEE Trans. Automat. Contr., vol. 37, pp. 1106–1118, Aug. 1992.

[12] Y. Guo, Z. P. Jiang, and D. J. Hill, "Decentralized robust disturbance attenuation for a class of large-scale nonlinear systems," Syst. Control Lett., vol. 37, pp. 71–85, 1999.

[13] Y. Tang, M. Tomizuka, G. Guerrero, and G. Montemayor, Decentralized robust control of mechanical systems, IEEE Trans. Automat.Contr., vol. 45, pp. 771–776, Apr. 2000.

[14] P. Krishmanurthy, and F. Khorrami, "Decentralized control of large-scale nonlinear systems in generalized output-feedback canonical form," In Proceedings of the 40th IEEE conference on decision and control, Orlando, pp. 1322–1327, 2001.

[15] B. Karimi, M.B. Menhaj, A. Afshar, and I. Saboori, A Decentralized Direct Adaptive Controller for a Class of Large-Scale Interconnected Nonlinear Systems, IEEE International Symposium on Intelligent Signal Processing, Madrid – Spain, Oct.,3-5, 2007.

[16] J. T. Spooner and K. M. Passino, "Adaptive control of a class of decentralized nonlinear systems," IEEE Trans. Automat. Contr., vol. 41,pp. 280–284, Feb. 1996.

[17] J. T. Spooner, and K. M Passino, Decentralized adaptive control of nonlinear systems using radial basis neural networks, IEEE Transactions on Automatic Control, 44(11), 2050–2057, 1999.